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The Relationship Between Social Care Resources and Healthcare Utilisation by Older People in England: An Exploratory Investigation

Maria Lucia Pace, Dan Liu,
Maria Goddard, Rowena Jacobs,
Raphael Wittenberg, Gerard McGonigal,
Anne Mason

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The relationship between social care resources and healthcare utilisation by older people in England: an exploratory investigation

[a]Maria Lucia Pace
[bc]Dan Liu
[b]Maria Goddard
[b]Rowena Jacobs
[d]Raphael Wittenberg
[e]Gerard McGonigal
[b]Anne Mason

[a]Università Cattolica del Sacro Cuore, Rome, Italy
[b]Centre for Health Economics, University of York, UK
[c]Centre for Health Economics Research and Evaluation (CHERE), University of Technology Sydney, NSW, Australia
[d]London School of Economics and Political Science, UK
[e]Department of Medicine for the Elderly, York Teaching Hospital NHS Foundation Trust, York, UK

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Background to series

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The CHE Research Paper series takes over that function and provides access to current research output via web-based publication, although hard copy will continue to be available (but subject to charge).

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Centre for Health Economics
Alcuin College
University of York
York,
YO10 5DD, UK
www.york.ac.uk/che

Abstract

Background Since 2010, adult social care spending has fallen significantly in real terms whilst demand has risen. Reductions in local authority (LA) budgets are expected to have had spill over effects on the demand for healthcare in the English NHS.

Motivation If older people, including those with dementia, have unmet needs for social care, their use of healthcare may increase.

Methods We assembled a panel dataset of 150 LAs, aggregating individual-level data where appropriate. We tested the impact of changes in LA social care resources, which was measured in two ways: expenditure and workforce. The effects on people aged 65+ were assessed on five outcomes.

1. Rates of emergency hospital admissions for falls in people with dementia aged 65 and over.
2. Rates of emergency hospital admissions for fractured neck of femur in people 65 and over.
3. Extended length of stay in people with dementia, 7 days and over
4. Extended length of stay in people with dementia, 21 days and over
5. Rates of NHS Continuing Healthcare (NHS CHC)

Outcomes (utilisation) data were derived from the Hospital Episode Statistics (1, 2, 3 and 4), the Public Health Outcomes Framework (2), and publicly available datasets from NHS Digital (5). Datasets varied in the timeframes available for analysis. Planned analysis of the effects of social care cuts on delayed transfers of care in mental health trusts, and on deprivation of liberty safeguards were not undertaken because of data quality concerns.

We tested the effect of two separate explanatory variables: adult social care gross current expenditure (per capita 65 and over) adjusted by area cost; and adult social care workforce staff (per capita 18 and over). Workforce measures distinguished LA and independent sector employees and included professional and non-professional staff providing direct social care. We ran negative binomial models and linear models, and controlled for a range of confounding factors, including deprivation, ethnicity, age, unpaid care, LA class and year effects. To account for potential endogeneity ('reverse causality'), we also tested the Area Cost Adjustment (ACA) as an instrumental variable and ran dynamic panel models. Sensitivity analysis explored the effects of the additional effects of the Better Care Fund.

Results The level of social care expenditure on older people was not significantly related to emergency admission rates for falls in people with dementia or for fractured neck of femur. Extended stays of 7 days or longer were significantly and positively related to the level of social care spend, but this association was no longer significant when additional spend from the Better Care Fund was taken into account. There was no significant relationship between the level of social care spend and hospital stays of 21 days or longer or between spend and uptake of NHS CHC.

We also tested the effect of four social care workforce measures. LAs employing higher rates of social care staff (especially professional staff) had significantly higher levels of NHS CHC, but there was no significant relationship between LA staffing levels and the remaining four outcomes. LAs with higher levels of independent social care staffing had significantly lower rates of extended stays, but there was no association with either emergency admissions or on NHS CHC. The effect of 'full time' unpaid care on outcomes was mixed, with tentative evidence of a protective effect on admissions for falls, and on extended stays of 21 days or longer.

When the Area Cost Adjustment was used as an instrument in place of expenditure, results were largely consistent with the main analysis: there were negative effects on NHS CHC but no effect on any other outcome. The dynamic panel models found a positive relationship between spend and emergency admissions for falls, but the effect on other outcomes was statistically insignificant.

Conclusions The study found no consistent evidence that reductions in social care budgets led to the expected rises in hospital admissions, hospital stays or uptake of NHS CHC. However, findings suggest that public sector staff providing direct social care, particularly professional staff, may be instrumental in facilitating access to NHS CHC. In addition, the study found tentative evidence that extended hospital stays are partially offset by social care provision by the independent sector and by unpaid carers providing intensive care. To test the validity and robustness of these findings, future research using linked individual-level health and social care data is needed.

Keywords: Social care, Healthcare, Dementia, Local authority, Cost Shifting

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Introduction

From 2010 to 2015, funding for adult social care was cut by £4.6bn which translates into a real terms reduction of 31% [1]. The cuts to Local Authorities (LAs) have coincided with a period when most councils faced both growing numbers of people in need and an increased complexity of need [1], driven in part by an ageing population [2].

In the 2017 Budget Statement, the chancellor announced an extra £2bn for social care, spread over three years, and empowered councils to raise additional funds through a hypothecated tax called the social care precept [3]. The aim was to ease pressure on hospitals whose older patients could not be discharged home due to a lack of community care, by meeting social care needs and providing short-term support to stabilise social care markets [4]. Whilst the measures were broadly welcomed, many considered them insufficient to close the funding 'black hole' [5].

The government planned to abolish general grant funding for LAs from 2020 [2], a move that would make budgets heavily reliant on council tax and business rates. With the costs of care for older adults projected to rise 4.4% annually in real terms over the next 20 years [6], a long-term, sustainable solution is needed on how care should be funded and provided [3]. The forthcoming Green Paper on care and support for older people [4] is expected to articulate options for the necessary system reforms. However, difficult decisions lie ahead: there is no easy way to square the circle [2, 5].

Funding reductions for adult social care may also have shifted costs of long-term care onto older people, or reduced the supply of care home beds or domiciliary care services in some areas. If the funding cuts increased unmet needs for social care in older people, there may have been increases in demand for healthcare services, such as emergency hospital admissions and delayed transfers of care (DToC) [7]. The link between the supply of social care and the demand for healthcare is complex and depends in part on the degree of substitution or complementarity between elements of social care and healthcare [8]. Whilst previous studies have examined the relationships between specific social services – usually long-term residential or nursing care – and healthcare utilisation [7-10], this study assessed the impact of broader area-based measures of social care spending and staffing rather than changes in the level of provision of individual services.

The overarching aims of our study are to explore the effects of changes in LA social care resources on older people in terms of healthcare utilisation and the use of NHS Continuing Care (NHS CHC). Where data permit, we focused on outcomes for people with dementia, as these individuals have complex needs that straddle the health and social care interface. The paper contributes to a growing literature exploring the interdependencies between social care and healthcare.

Methods

Data

Details of the datasets used are in Table 1.

Table 2 provides summary statistics for the outcomes, explanatory variables and control variables. The level of analysis is the LA. Where necessary, we aggregated individual level data to construct LA level data.

Table 1: Data Sources and derivation of outcomes and explanatory variables

Dataset	Reporting level	Year	Type of variable(s) derived	Details of variables	Source
Area Cost Adjustment	LA level[1]	2011/12 2013/14	Explanatory variable: adjuster for Adult Social Care expenditure Instrument for IV analysis.	Multiplier used to increase social care budgets in areas where labour input costs are higher. Inverse of multiplier used to make fairer expenditure comparisons across LAs	DCLG Methodology Guides [11, 12].
Better Care Fund (BCF) Reports	LA level	2014/15 (Q4 only) 2016/17	Explanatory variable: expenditure from pooled funds	Numerator: total actual BCF expenditure per annum per LA Denominator: mean annual counts of working age LA residents claiming DLA or PIP plus LA population aged 65+	https://www.england.nhs.uk/ourwork/part-rel/transformation-fund/bcf-plan/
Carers Allowance (CA)	LA level	2009/10 2017/18	Explanatory variable: numerator for carer prevalence	Numerator: mean annual counts of LA residents aged 18-64 who were receiving or entitled to CA. Denominator: LA population aged 18-64	https://stat-xplore.dwp.gov.uk
Disability Living Allowance (DLA)	LA level	2009-2016	Explanatory variable: denominator for Better Care Fund (BCF) spend. From 2013, DLA gradually replaced by PIP	Denominator for per capita spend on the BCF: mean annual counts of working age LA residents claiming DLA or PIP plus LA population aged 65+	https://stat-xplore.dwp.gov.uk/webapi/jsf/login.xhtml
Hospital Episode Statistics (HES)	Personal level	2009/10-2016/17	Dependent variable: extended stays Dependent variable: numerator for emergency admissions for falls / FNF	Extended stays: Indicator 1: the proportion of spells with length of stay of seven days or more among all spells. Indicator 2: the proportion of spells with length of stay of 21 days or more among all spells. Emergency admissions: 1. Falls in people with dementia [all years]	HES accessed via Data Sharing Agreement with NHS Digital.

[1] The ACA covers 'fringe' areas composed of shire districts. See text for how ACA values were converted to values for upper tier LAs.

Dataset	Reporting level	Year	Type of variable(s) derived	Details of variables	Source
				2. Fractured Neck of Femur (FNF) (2009/10 only).	
Cognitive Function and Ageing Study II (CFAS II)	Residential setting	2008 –2011	Dependent variable: denominator for emergency admissions for falls	Emergency admissions for falls in people with dementia: used to derive expected dementia registers.	Matthews et al. 2013 [13].
Numbers of Nursing Home GP Patients by practice in England	GP practice	2006/07 – 2016/17	Dependent variable: denominator for emergency admissions for falls	Emergency admissions for falls in people with dementia: used to derive expected dementia registers.	2006/07 to 2012/13 data supplied by NHS England NHS Digital archives: 2013/14 data 2015/16 – 2016/17 data
ONS – census data	Residential setting	2011	Dependent variable: denominator for emergency admissions for falls	Emergency admissions for falls in people with dementia: used to derive expected dementia registers.	ONS website
General and Personal Medical Services dataset (GMS)	GP practice	2009/10 – 2016/17	Dependent variable: denominator for emergency admissions for falls	Emergency admissions for falls in people with dementia: used to derive expected dementia registers.	GMS (2009/10 to 2012/13) were accessed via a Data Sharing Agreement with NHS Digital. GMS (2013/14-2016/17) is available online.
Local authority (LA) revenue expenditure and financing England (outturn data - RO3 – SOCIAL CARE)	LA level	2008/09 2016/17	Explanatory variable: numerator for per capita gross current expenditure	Numerator (to 2014/15): social care expenditure for people 65+ including those with mental illness Numerator (from 2014/15): social care expenditure for people 65+ (sum of 5 subcategories)	https://www.gov.uk/government/collections/local-authority-revenue-expenditure-and-financing
Mapping files	CCG to LA mapping	2014	Used to convert CCG counts to LA counts, based on share of LSOA.	Outcome variable: NHS Continuing Healthcare (counts for numerator and denominator)	https://www.local.gov.uk/sites/default/files/documents/mapping-ccgs-hwbs-and-hwb-507.xlsx

Dataset	Reporting level	Year	Type of variable(s) derived	Details of variables	Source
Mental health minimum data set (MHMDS)	Personal level	2011/12 2016/17	Dependent variable (DToCs): numerator and denominator	[This outcome was not analysed due to poor data quality; see text for details]	Accessed via Data Sharing Agreement with NHS Digital
National minimum data set for social care (NMDS-SC)	LA level	2012/13 2016/17	Explanatory variable: numerator for staffing measures	Terciles: per capita 18+ whole time equivalent (WTE) direct care staff (excl. professionals) of LA social services; Terciles: per capita 18+ WTE direct care staff (incl. professionals) of LA social services; Terciles: per capita 18+ WTE direct care staff (excl. professionals) of social services in the independent sector. Terciles: per capita 18+ WTE direct care staff (incl. professionals) of social services in the independent sector.	Accessed via Data Sharing Agreement with Skills for Care
NHS Continuing Healthcare (NHS CHC): Snapshot Eligibilities	CCG level	2013/14 2016/17	Dependent variable: numerator for NHS continuing care Dependent variable: denominator for NHS continuing care	Numerator: mean annual counts of those receiving or entitled to NHS CHC Denominator: mean annual counts of those aged 18+ (constructed from GP registers)	https://digital.nhs.uk/data-and-information/publications/statistical/nhs-continuing-healthcare-activity
Personal Independence Payment (PIP)	LA level	2013 2016	Explanatory variable: denominator for Better Care Fund (BCF) spend. From 2013, DLA gradually replaced by PIP.	Denominator for per capita spend on the BCF: mean annual counts of working age LA residents claiming DLA or PIP plus LA population aged 65+	https://stat-xplore.dwp.gov.uk/webapi/jsf/login.xhtml
Population estimates summary for the UK	LA level	2010/11 2016/17	Explanatory variable: denominator for per capita adult social care	Denominator for per capita spend: total population aged 65+	https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandand
	LA level	2010/11 2016/17	Explanatory variable: denominator for per capita Better Care Fund (BCF) spend	Denominator for per capita spend on the BCF: working age claimants of DLA / PIP + population 65+.	
	LA level	2010/11 2016/17	Outcome variable: denominator for emergency admissions for FNF	Denominator for FNF admissions: total population aged 65 +	

Dataset	Reporting level	Year	Type of variable(s) derived	Details of variables	Source
	LA level	2010/11 2016/17	Explanatory variable: denominator for staffing measures	Denominator for staffing: total population aged 18 +	walesscotlandandnorthernireland
	LA level	2010/11 2016/17	Explanatory variable: denominator for carer prevalence	Denominator for Carers Allowance claimants: total population aged 18-64	
Public Health Outcome Framework	LA level	2015	Explanatory variable: IMD	IMD: Index of Multiple Deprivation score in 2015	https://fingertips.phe.org.uk/profile/public-health-outcomes-framework
	LA level	2011	Explanatory variable: ethnicity	Ethnicity: the proportion of the population from black and minority ethnic (BME) groups	
	LA level	2010/11 2016/17	Dependent variable: Emergency hospital admissions due to fractured neck of femur (FNF) [2010/11 to 2016/17 only]	Emergency admission rates due to FNF in people aged 65+ per 100,000 population. [PHOF methodology used with HES to derive values for 2009/10]	

Notes: BCF: Better Care Fund; BME: black and minority ethnic; CA: Carers Allowance; CCG: Clinical Commissioning Group; CFAS II: Cognitive Function and Ageing Study II; FNF: Fractured Neck of Femur; GMS: General and Personal Medical Services dataset; HES: Hospital Episode Statistics; IMD: Index of Multiple Deprivation; LA: Local Authority; MHMDS: Mental Health Minimum Data Set; NHS CHC: NHS Continuing Healthcare; NMDS-SC: National Minimum Data Set for Social Care; ONS: Office for National Statistics; PIP: Personal Independence Payment; WTE: whole time equivalent.

Table 2: Descriptive Statistics (annual values)

Variable	Years		Mean	SD	Min	Max	N
OUTCOMES							
FNF admissions (all), rate per 100,000 65+ [a]	2009/10-2016/17	FNF adm rate	607.4	74.7	287.5	1063.8	1204
		FNF, count	372.4	333.5	<6	1882	1204
		Pop 65+	60786.9	54098.3	470	305924	120
Falls admissions rate per 1000 w dementia	2009/10-2016/17	Falls adm rate	120.0	35.1	31.6	256.8	1216
		Falls, count	459.6	395.7	<6	2415	1216
		Pop w dementia [b]	4,066	3,696	26	19,478	1216
% extended stays, rate (of all stays)	2009/10-2015/16	7+ days	38.9	5.8	21.0	57.6	1064
		21+ days	15.3	3.2	5.5	27.6	1064
NHS CHC, rate per 50,000 18+	2013/14-2016/17	Rate eligible	67.5	30.3	11.9	236.1	608
		Eligible, count	396.7	325.2	<6	1,734	608
		LA pop 18+ [b]	297,701	221,069	1,388	1,226,405	608
SOCIAL CARE							
Social care expenditure, adjusted (£)	2009/10-2016/17	Gross current expenditure per 65+	948.2	302.28	5.9	2497.4	1214
BCF per 1000	2015/16- 2016/17	BCF spend per 1000 [18-64 with disability; or 65+]	539.9	539.1	195.2	4941.9	300
LA WTE staff per 1000 pop 18+ [c]	2012/13-2016/17	Direct care	1.21	0.75	0	4.86	753
		Direct care incl. professionals	1.65	0.83	0	5.69	753
Independent sector WTE staff per 1000 pop 18+		Direct care	14.04	4.63	6.55	78.93	755
		Direct care incl. professionals	14.91	4.79	6.80	80.39	755
CONTROLS							
Deprivation [d]	2015	IMD 2015	23.01	8.07	5.65	42.00	1216
Ethnicity	2011	% BME	16.36	16.22	1.18	71.03	1216
Age groups	2009/10-2016/17	% 65 to 74	8.76	2.28	3.18	15.14	1216
		% 75 to 84	5.40	1.35	2.00	9.02	1216
		% 85+	2.18	0.64	0.71	4.18	1216
Informal care	2009/10-2016/17	'Full time' carers per 1000 pop 18-64	18.85	7.10	2.93	46.88	1216

Note: Values are for the whole dataset, not for estimation samples (which vary across models). BCF: Better Care Fund; BME: Black and minority ethnic; FNF: fractured neck of femur; NHS CHC: NHS Continuing Healthcare; SD: standard deviation; WTE: whole time equivalent. Small numbers suppressed to protect against disclosure.

a. In all years, the PHOF has missing values for City of London and Isles of Scilly. In 2016 there are also missing values for Nottingham and Nottinghamshire.

b. Counts are from GP lists

c. In 2013 and 2014, values for Norfolk are missing. The Isles of Scilly has been included with Cornwall for all years of WTE staff data. In 2012-2015, LAs in Torbay and NE Lincolnshire employed no social care staff.

d. The deprivation score ranges from 0-100, with higher scores indicating higher levels of deprivation

Outcomes (healthcare utilisation)

We analysed five dependent variables that captured different types of healthcare utilisation: emergency admissions for falls and for fractured neck of femur; extended stays for 7 or more days, and for 21 or more days; and NHS CHC. We considered two additional outcomes for which the data were insufficiently robust to allow a meaningful analysis: delayed transfers of care for people with dementia treated in mental health hospitals; and Deprivation of Liberty Safeguards.

Emergency hospital admissions for falls

This measure captures emergency admissions due to falls in people with dementia aged 65 and over. This outcome is more common in people with dementia [14] and is a 'front door of the hospital' metric that could plausibly be influenced by the supply of social care. The rate of emergency falls in people 65 and over is a national indicator from the Public Health Outcomes Framework (PHOF) and is expressed as a rate per 100,000 persons within each LA. We used the PHOF indicator definition, but restricted the measure to people with dementia using the Hospital Episode Statistics (HES) data (2009/10 to 2016/17). Admission for people with dementia were identified based on a list of ICD10 codes from our previous work [15]. Rates were expressed per 1000 persons on GP dementia registers.

Emergency hospital admissions for fractured neck of femur

People admitted for the treatment of femoral neck fractures (FNF) are a subset of those who have suffered a fall. Our advisory group recommended this measure because hospital coding of FNF is considered better than coding of falls. We were also advised that dementia is often undercoded for inpatients. Like the admissions rate for falls, hip fractures in people aged 65+ is a PHOF indicator and is expressed as a rate per 100,000 persons within each LA (2010/11 to 2016/17). For 2009/10, we constructed the same indicator from the HES data using the PHOF indicator definition.

Extended stays

We used two measures of extended stay [16], both of which include emergency and elective admissions for patients aged 65+ who were coded as having a diagnosis of dementia [15]. The first measure is the percentage of spells with a length of stay of at least seven days or more. The second one is the percentage of spells with length of stay of 21 days or more. In both cases, the denominator was the total number of spells for this patient group (i.e. all spells regardless of length of stay).

We used the HES data from 2009/10-2016/17 and constructed spell level data. A spell is defined as the period from admission to discharge within a hospital and the spell may or may not include multiple episodes. We used all spells from the date when a patient was first diagnosed with dementia, i.e. all spells with admission date at or after diagnosis. Spells beginning before April 1, 2009 and spells starting after March 31 2016 were excluded. We used 2016/17 data only to calculate the length of stay of unfinished spells beginning before March 31, 2016.

NHS Continuing Healthcare

'NHS Continuing Healthcare' (NHS CHC) is a package of ongoing care that is arranged and funded solely by the NHS. Individuals must be aged 18 or over and have a 'primary health need' [17]. There are no limits on the type of service covered or the settings in which the package of support is delivered, so support may include social care that would normally be funded by LAs. Financial pressures on LAs could lead to an increase in the use of NHS CHC. However, concerns over the capacity of NHS CHC to bridge the gap have been expressed [18].

As NHS CHC is funded by the NHS rather than by LAs, data are reported at the CCG level. We therefore used a mapping file to estimate the relevant numerators and denominators. For the numerator, we converted counts of eligible and newly eligible patients from CCG to LA level, based on the proportion of Lower Layer Super Output Areas (LSOAs) within a CCG that was covered by a LA. We used the same approach for the denominator, which was the counts of adults aged 18+ derived from general practice lists. During our study period, 181 CCGs mapped to a single LA: of these, 86 were a one-to-one mapping and the other 95 CCGs mapped many-to-one LA. The remaining 30 CCGs had an overlap with more than one LA.[2]

We calculated the rate of eligible and newly eligible LA patients per 50,000 population aged 18+, and computed financial year values as a mean of the quarterly values.[3]

Outcomes excluded from the analyses

Deprivation of Liberty Safeguards (DoLS)

Another potential impact of financial pressures on LA social care budgets is an increase in the use of involuntary restraints under the Mental Capacity Act 2005, i.e. deprivation of liberty safeguards (DoLS) [19].

Introduced in 2008, DoLS are an extra safeguard to the Act to ensure people who cannot consent to care arrangements in a care home or hospital are protected if these arrangements deprive them of their liberty [20], including protection from harm [19].

A potential result of financial pressures on social care budgets is that there may be fewer staff to care for a relatively larger number of clients. One way of managing individuals with challenging behaviours is the use of involuntary restraints. If staff do not have time to support these individuals, they may resort to DoLS as a coping mechanism.[4]

Data are available from 2009/10, and report the number of applications authorised, completed or not granted within each LA in each year. The relevant variable for our study is the number of applications authorised. From 2014/15 onwards, data were rounded to the nearest five significant figures and small values were suppressed; we replaced suppressed values with a random integer between 0 and 5.

Figure 1 shows the trend in DoLS, which increases sharply in 2014/15. A ruling in the Supreme Court in March 2014 (the 'Acid Test') led to a wider interpretation of deprivation of liberty and broadened the locations in which DoLS could occur to include community and domestic settings where the State was responsible for the arrangements [21]. In 2014/15, the number of DoLS applications rose 10-fold and many LAs struggled to process applications within the legal time limit [21].

[2] E.g. NHS South Tees CCG covers two unitary authorities. The CCG encompasses 174 LSOAs of which 86 (49%) are in Middlesbrough LA and 88 (51%) are in Redcar and Cleveland LA. We used these proportions to estimate each LA's share of the CCG's NHS CHC eligible patients. This assumes patients are distributed evenly across LSOAs, which may not be the case.

[3] Quarterly data were available.

[4] Our advisory group suggested this potential impact.

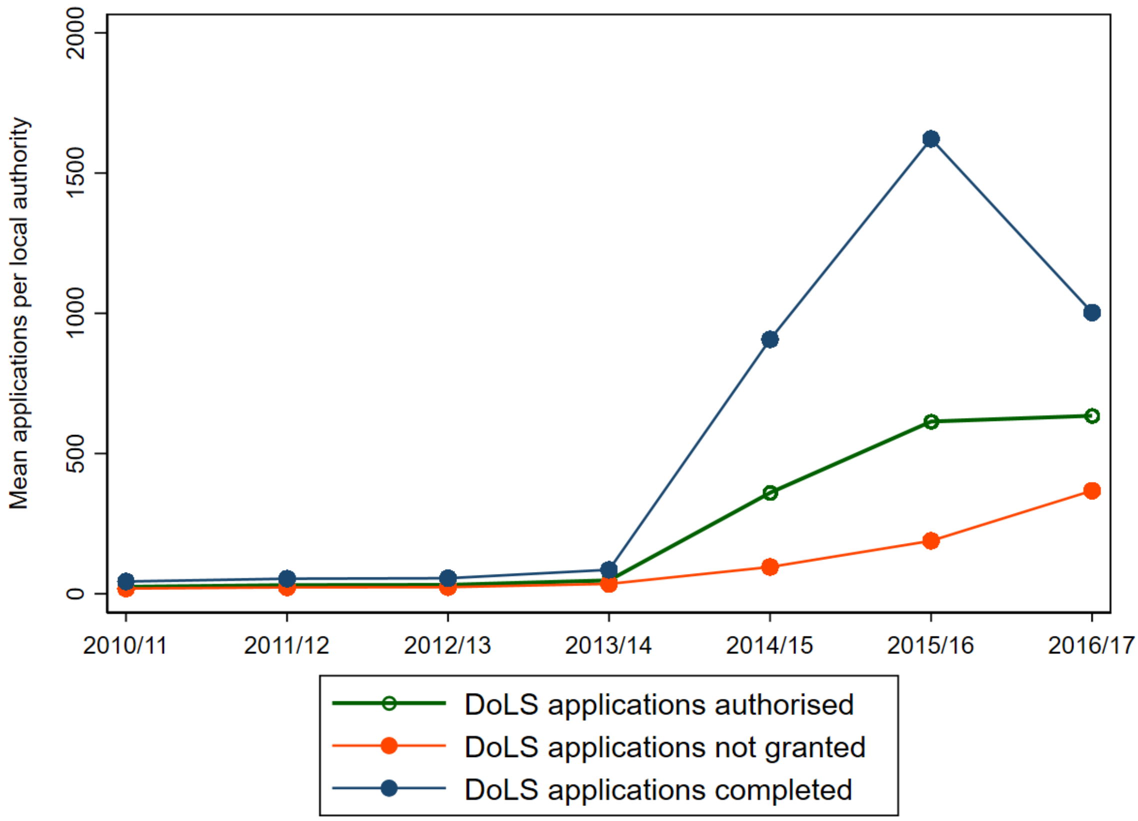

Figure 1: Trends in Deprivation of Liberty Safeguards (DoLS)

We considered whether to restrict the analysis to the count of authorised DoLS from 2014/15 onwards. DoLS can occur in hospitals or care homes, but only those arising in NHS settings are relevant for our study. Unfortunately, this information is not reported and so DoLS were not analysed further.

Delayed Transfers of Care (DToCs)

DToCs are a type of 'back door of the hospital' metric. Other studies have examined DToCs at the LA [7] or NHS Trust level [8, 9]. Our aim was to use individual level data from the Mental Health Minimum Dataset (MHMDS)[5] to assess DToCs affecting people with dementia treated in mental health trusts.

We calculated the total annual number of days of DToC within an LA (or the annual number of people whose discharge was delayed) and divided this by the total annual days of inpatient stay (or the total number of people experiencing an inpatient stay per annum). We considered DToCs only for which LAs were wholly or partly responsible (i.e. we excluded those where the NHS was responsible[6]). We derived LA-level measures by aggregating individual-level data from the MHMDS. We restricted our sample to individuals with cognitive impairment only (low need), or cognitive impairment or dementia (moderate need, high need, high physical need or engagement) as defined by the 'cluster'[7] to which they were assigned.

[5] The MHMDS has been renamed twice in recent years to reflect its broadening scope. We use the name used during our study period.
[6] We excluded cases where the delay discharge reason was "await further non-acute NHS care" or "housing patient not covered by NHS & Community Care Act".
[7] Mental health clusters are the mental health equivalent of Diagnosis Related Groups used in acute care. There are 4 clusters for organic mental illness (i.e. dementia).

Owing to numerous quality concerns with the data, this outcome was not analysed further.
The first data quality issue was that the numbers of DToCs per LA were unexpectedly low. LAs reported around 500 days of delay annually, equating to approximately four individuals subject to a delay over the whole year (Table 3). An analysis by Gaughan and colleagues [7] of all social-care related DToCs from 2009 to 2013 reported a mean LA value of 236 days per month, with an average of 8.5 patients awaiting a transfer of care on the monthly census date.[8] Further work by the same authors showed that Mental Health Trusts typically had more DToCs than Acute Trusts, and these delays were more commonly due to a lack of social care [9].

Table 3: Trends in DToCs in MH Trusts: days and persons

		Persons delayed in MH Trusts, by LA							Days delayed in MH Trusts, by LA				
		mean	sd	min	max	N			mean	sd	min	max	N
2011/12		3.73	4.68	1	30	70			554.31	630.29	8	3709	70
2012/13		5.79	5.74	1	26	81			629.09	681.65	3	3018	81
2013/14		4.39	4.31	1	23	90			495.19	457.67	1	1915	90
2014/15		2.75	2.53	1	13	73			162.29	195.90	8	1030	73
2015/16		1.67	1.44	1	6	27			286.19	208.01	5	682	27
2016/17		5.28	6.20	1	33	87			636.10	775.14	1	5095	87
TOTAL		4.28	4.90	1	33	428			488.88	595.58	1	5095	428

Second are even more serious data concerns. Whereas the Gaughan study [7] had data from 147 LAs, many LAs in our study did not report any delayed discharges in MHMDS. Table 3 shows that at most 90 LAs (59%) reported any DToCs arising in a mental health trust in a year. We cannot be sure whether this reflects a quality issue[9] or a true absence of delayed discharges in those specific LAs.

The third issue with the MHMDS is the absence of data from part of the financial year 2015/16. Owing to a change in the data collection, the last available data for 2015/16 are for 30 November 2015. Therefore, four months of data are missing in this financial year.[10] The missing data were subsequently added to the MHMDS for 2016/17, although only 27 LAs (18%) reported data for 2015/16 (Table 3).

The data were therefore insufficiently robust to allow a meaningful analysis.

Measuring changes in social care supply

We considered two explanatory variables to capture changes in social care resources: expenditure on social care for people aged 65 and over, and social care staff for people aged 18 and over. We also considered a third measure of activity/utilisation by people aged 65 and over which was not included in analysis. Given the potential endogeneity ('reverse causality') problems with these three measures, we also used instrumental variables to capture changes in social care supply.

Expenditure on social care

We used per capita LA expenditure on social care for adults 65 and over as our main explanatory variable.

LA revenue expenditure is reported annually with specific categories for social care spend.

[8] i.e. on the census day, which occurs once a month.
[9]Relating to this issue, the Mental Health Bulletin 2016-17 reported a quality issue in the submission from the North East London NHS Foundation Trust, which after the revised submission makes a large change to patient numbers.
[10] Mental Health Bulletin 2015-16, Annual Report.

We compiled data on gross current expenditure (GCE) on social care for people 65 and over for financial years 2009/10 to 2016/17. GCE is defined as total current expenditure (spending on staff and running expenses) less income from the NHS (or from joint arrangements for example) but includes income from client contributions (sales, fees and charges). We chose GCE as our explanatory variable because this is the fiscal metric commonly used to denote government spending [22], and takes account of local capacity to raise funds from clients.

There is a reporting discontinuity in 2014/15 regarding the expenditure category of Adult Social Care. Until 2014/15, there was only one category for social care expenditure for people 65 and over: 'Older people (65 and over) including older mentally ill'. From 2014/15 onwards, in conjunction with changes in the collection of Social Care Activities data,[11] expenditure on people 65 and over was reported under five categories:

i. Physical Support - older people (65+)
ii. Sensory Support - older people (65+)
iii. Learning Disability Support - older people (65+)
iv. Support for Memory and Cognition - older people (65+)
v. Mental health support - older people (65+)

To derive comparable measures of expenditure to previous years, we summed the five categories. We computed per capita values using data on LA populations aged 65 and over. We then deflated expenditure using the Area Cost Adjustment to reduce differences in LA purchasing power (Figure 5).

Area Cost Adjustment

The Area Cost Adjustment (ACA) is used to adjust LA budgets in recognition of higher cost of inputs in London and certain parts of the South-East compared with the rest of England [23]. The ACA reflects differences in labour costs and business rates, with only the labour cost adjustment (LCA) used to adjust allocations for adult social care [11].[12] As adult social care budgets have been multiplied by the LCA, we converted LA expenditure back to unadjusted values in order to make fair comparisons across LAs. For example, if London authorities face higher input prices than other parts of the country this means that £100 in London has a lower purchasing power than elsewhere. Therefore, the effect of an increase in spend per person of £1 may differ because of purchasing power differences rather than because the effects on outcomes are different.

ACA values are available for 2011/12 and for 2013/14,[13] and take a value of 1 for 'average' areas and a value above 1 for higher cost areas [11, 12]. We converted these to LCAs by multiplying the additional value above 1 by 0.65 based on the approach set out in the ACA methodology guides [11, 12]. Some ACA areas map one-to-one onto a LA. Other areas map to multiple LAs (or parts of them) and some LAs map to multiple ACA areas [24]. We therefore constructed a panel dataset of all LAs (including the districts that are the lower tier authorities within the upper tier shire counties), and merged this with LCA values. For LAs without a straightforward 1:1 mapping, we calculated a weighted average LCA value using population size as the weights.

In a separate analysis, the ACA was also used as an instrument (see section 'Instrumental variables').

[11] In 2014, SALT (Short and Long Term Support) replaced both ASC-CAR (Adult Social Care Combined Activity Return) and RAP (Referrals, Assessment and Packages of Care). There is a discontinuity between these two collections and the collection format changed.

[12] The LCA factor is weighted by the estimated labour share for each 'block' of services. For adult social care, the weight is 0.65.

[13] ACA values have not been updated since 2013/14. We used 2011/12 values for 2011/12 and 2012/13, and 2013/14 values for the remaining years of our study.

Social Care Staff

We used four whole time equivalent (WTE)[14] measures of staffing[15] and derived per capita values using the LA population aged 18 and over.[16] To test for non-linearity, we converted them to terciles, i.e. low, medium and high levels, with low levels of staffing as the reference category.

a) WTE LA adult social care sector staff: direct care
b) WTE LA adult social care sector staff: direct care and professional staff
c) WTE independent sector adult social care staff: direct care
d) WTE independent sector adult social care staff: direct care and professional staff

Workforce data came from the National Minimum Dataset for Social Care (NMDS-SC). The data provider, Skills for Care, provided WTE estimates of four groups comprising the adult social care workforce[17] and we based our measures on two 'front-line' groups with care providing roles. Direct care staff includes care workers, community support workers and personal assistants. Examples of professional direct care staff are allied health professionals, registered nurses, occupational therapists and social workers. Breakdowns by client group (e.g. older people) are not available.

Measures of social care excluded from the analysis

Activity measures

Activity datasets provide information on utilisation of social care for different client groups. However, there were changes in the data collection forms in 2014/15 that made it difficult to derive consistent estimates over time. Prior to 2014/15, activity data were collected using two forms:

1 Referrals, Assessments and Packages of Care return (RAP)
2 Adult Social Care Combined Activity Return (ASC-CAR).

These were combined with the Personal Social Services Expenditure and Unit Costs Return (PSS-EX1) to produce reports on social care activity. From 2014/15, the Short and Long Term (SALT) Return replaced these datasets. Of the available measures, only the one based on receipt of residential care appears reasonably consistent over time. However, we decided not to use this measure as it only captures partial changes in social care supply.

Control variables

To control for confounding factors, our models also included a measure of deprivation (the Index of Multiple Deprivation score (2015)), and the percentage of the LA population who were of Black and Minority ethnicity (BME) originally sourced from the Census (2011). These two control variables were reported in the PHOF. We also controlled for the age structure of the LA population (percentages aged 65-74, 75-84 and 85+), and included LA class [18] and year effects.

We also controlled for the supply of unpaid care. As a sensitivity analysis, we adjusted for per capita spend on the Better Care Fund (both explained below).

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[14] WTE is constructed by dividing contracted hours by 37 and treating anyone with more than 37 contracted hours as 1 WTE.
[15] Staffing numbers are estimates produced by Skills for Care
[16] The NMDS-SC does not report numbers of staff working with older people
[17] NMDS-SC includes two additional job groups who do not provide care: managerial and 'other' (e.g. administrative or ancillary staff or other non-care providing roles)
[18] There are 4 classes of LAs with responsibility for social care: London boroughs; unitary authorities; shire counties; and metropolitan boroughs. We used unitary authorities as the reference category.

Unpaid care

The supply of unpaid care was proxied using quarterly benefits data from the Department of Work and Pensions. Carer's Allowance (CA) is a non-contributory benefit for people who:

- look after a severely disabled person [19] for at least 35 hours a week
- are not gainfully employed, and
- are aged 16 or over and not in full-time education.

Some claimants are entitled to CA, but do not receive a payment because of the 'overlapping benefits' rule, i.e. they receive another benefit or State Pension that is equal to or greater than their weekly rate of CA. Combining counts of benefit recipients and counts of those entitled to CA who do not receive payments gives a more complete picture of the prevalence of informal carers in each LA. The rate of individuals of working age providing informal (unpaid) care has risen steadily over time. The box plot (Figure 2) shows median values, the interquartile range and maximums.

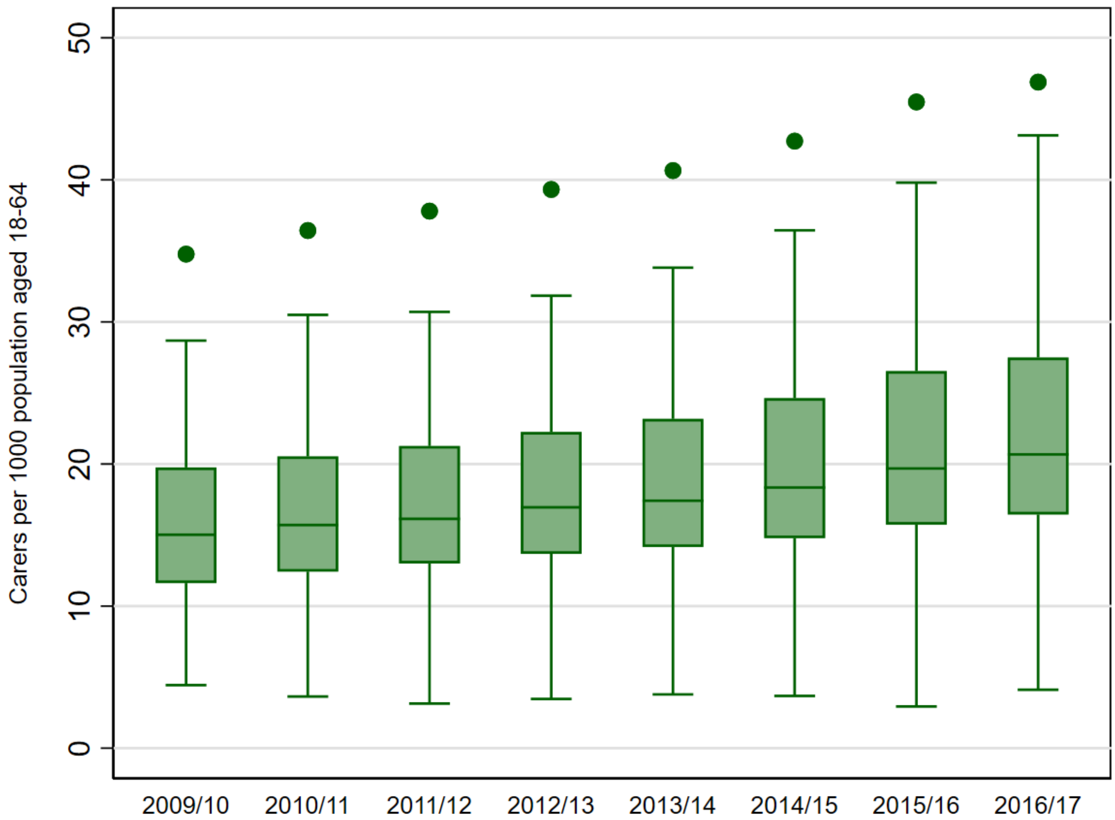

Figure 2: Trend in the LA rate of 'full time' working age unpaid carers per 1000 population

For the numerator, we calculated the mean annual values of all entitled cases aged 18 to 64 in each LA. For the denominator, we used LA populations aged 18 to 64. The resulting rate captures proportion of 'full-time' unpaid carers of working age, and excludes those providing lower levels of unpaid care or older people providing unpaid care. The measure can therefore be viewed as the 'tip of the iceberg' of unpaid care.

[19] Care recipients need to be in receipt of one of three benefits (Attendance Allowance (AA); medium or high rates of DLA or PIP; or 'Constant AA').

Better Care Fund

Introduced in 2015/16, the Better Care Fund (BCF) is to date the only mandatory policy to support integration [25]. Health and social care funds are pooled into local budgets so that CCGs and LAs can jointly agree plans on how to spend the funds (£5.3bn in 2015/16, £5.8bn in 2016/17). The NHS must contribute a minimum level of funds to adult social care and many areas choose to pool more than required. Spending should improve performance on four metrics: DToCs, non-elective admissions, admissions to care homes, and reablement. From 2017, a new grant for adult social care known as the Improved BCF (iBCF) was also pooled with the BCF. This money must not be offset against the NHS minimum contribution [25] and is allocated to LAs using a methodology that gives more funds to councils with less capacity to raise funds through taxation [26].

The BCF therefore provides additional funds for adult social care and analyses should adjust for its effects. However, the BCF is targeted not only at older people but also at those with disabilities [27] so per capita values should not simply be added to adult social care expenditure for people 65 and over. In addition, only two years of BCF data are available (Table 1). Therefore, we derived per capita values based on the sum of LA population over 65 and the number of people in working age entitled to disability living allowance (DLA) or to personal independence payments (PIP). Given the short duration of the BCF per capita spend variable, the effect was tested in a sensitivity analysis.

Control variables excluded from the analysis

CQC ratings

We considered CQC ratings as another potential control variable. If the quality of care homes in a locality is poor, this could be indicative of a lack of appropriate social care options in a locality. However, it may reflect other factors including downward pressure on revenues resulting from competition in local markets [28], poor management, or difficulties in recruiting and retaining good quality social care staff. CQC care home ratings are therefore an indicator of multiple problems in the supply of social care and so are an imperfect measure for capturing shortages of care home beds as an underlying driver of extended stays.

Intermediate care beds

The availability of intermediate care beds could also drive extended stays and DToCs [29]. There have been regular national audits since 2012, but data are not in the public domain. Therefore, it was not possible to control for this factor.

Services for challenging behaviours

The availability of specialist services to support individuals with challenging behaviours is another potential reason for extended stays in people with dementia. However, specialist mental health secondary services are provided by the NHS and reflect NHS budgets rather than social care budgets.

Modelling and analysis

For the count outcome variables, we used random effects negative binomial models (RENB) to deal with overdispersion [30]. The RENB model [20] [30, 31] assumes that the count of the outcome (e.g. number of hospital stays of 7 days or longer) in local authority i and year t follows a Poisson distribution with parameter $\tilde{\lambda}_{it}$ which in turn follows a gamma distribution gamma(λ_{it},δ_i) where λ_{it} is specified as in equation 1.

[20] Hausman et al's (1984) negative binominal model is incorporated in several software packages such as Stata and SAS (Green, 2007). This paper used Stata for data analysis.

$$\lambda_{it} = exp\left(\beta_1 m_{it} + \beta_2 x_{it} + \beta_3 T_t + \ log\left(W_{it}\right)\right) \quad (1)$$

In the above, m_{it} is the main explanatory variable (expenditure or staffing); x_{it} includes local authority level covariates; T_t is a set of dummy variables for year effects; and W_{it} is an exposure term. The RENB model introduces randomness both across LAs and across years. For a given LA even if the observed covariates do not change over time, the counts are drawn from Poisson distributions with different parameters $\lambda_{1t},...,\lambda_{it}$.

The parameter δ_i is included as a random effect that varies randomly across LAs to capture unobserved and time invariant features of LAs. To integrate the parameter δ_i out of the marginal probability, Hausman et al. (1984) used a beta distribution with parameters a and b for the ratio $\delta_i / (1+\delta_i)$ [31].

We ran separate RENB models to test the effects of LA expenditure and LA social care staffing levels on five outcomes: NHS Continuing Care, extended stays (7+ days and 21+ days), and emergency admissions (for falls in people with dementia aged 65 and over, and for fractured neck of femur in the local population aged 65 and over).

Instrumental variables

The levels of LA expenditure and staffing for adult social care in part reflect the level of need for health and care in the local area. For example, an area with persistently high levels of extended stays may put more resources into adult social care to tackle the problem. This means there is a potential problem with ‘reverse causality’: higher spend may be associated with worse outcomes not because more money causes poorer performance but because historically poorer performance has called for higher levels of spend. In this case, if the level of spend is used as an explanatory variable then it will be correlated with the error term and estimates will be biased. A potential solution is the use of instrumental variables.

Previous studies have used elements of the funding formula as an instrument for examining the impact of NHS expenditure on outcomes [32], so we explored whether a similar approach might be feasible for deriving an instrument for social care supply.

Social care funding is allocated to LAs using a formula to account for differences in LAs’ ability to provide services where differences are due to exogenous factors [33]. First introduced in 2006/07, the current version is the relative needs formula (RNF) [23]. The formula captures the proportion of total need for all LAs and is derived by quantifying the relationship between spend and outcomes using data at the small area level [23]. For older people’s adult social care, the formula includes a basic amount per client, then top-ups for age, deprivation, low income, and sparsity. Finally, the total is adjusted for differences in labour costs (the ACA) [34].

We considered the elements of the funding formula as potential instruments, but age, deprivation, low income and sparsity are all related to our outcomes (i.e. measures of utilisation). However, ACA is suitable as a potential instrument using linear models (xtivreg in Stata).

Using the continuous outcome variable (rates), we employed linear random effects models. We estimated the following equations:

$$\widetilde{m}_{it} = \beta_0 + \beta_1 z_{it} + \beta_2 x_{it} + \beta_3 T_t + g_i + v_{it} \quad (2)$$

$$y_{it} = \beta_0 + \beta_1 \widetilde{m}_{it} + \beta_2 x_{it} + \beta_3 T_t + u_i + e_{it} \ (3)$$

where eq. (2) represents the first stage of the instrumental variable regression, in which we are estimating the endogenous variable $\widetilde{m}_{it}$using the chosen instrument, named z_{it}. Then, eq. (3) corresponds to the second stage, where y_{it} is the outcome variable; β_0 is a constant; $\widetilde{m}_{it}$ is the main endogenous control variable (per capita current gross expenditure) instrumented and estimated in the first stage (eq. (2)); x_{it} includes local authority level covariates; T_t is a set of dummy variables for year effects; u_i (g_i) is introduced to capture LA specific time invariant effects and follows a normal distribution; e_{it} (v_{it}) follows a normal distribution and is independent of u_i.The compound error term ($u_i + e_{it}$) is independent across LAs but not within an LA. To account for within-LA serial correlation, we clustered standard errors at the same level as the random effect (i.e. at the LA level) [35, 36]. All analyses were undertaken using Stata 14.2 (StataCorp LP).

Dynamic panel model

The dynamic panel model is a good alternative way to deal with the endogeneity issue in a panel model when good instruments outside of the model are not available. Furthermore, they are better at characterizing the economic relationship involving a dynamic adjustment process by including the lags of the dependent variable. It seems plausible that past values of emergency admission in a local area affects the values at time t. It is also plausible that both measures of extended stays and uptake of NHS continuing healthcare depend on their past values. Finally, people receiving NHS continuing healthcare may do so for more than one year, reinforcing persistent local trends. The positive and significant coefficient for the lagged dependent variable confirms these dynamics.

Given the presence of the autoregressive parameter, this model is estimated using the Generalized Method of Moments (GMM), which produces consistent parameter estimates for a finite number of periods, T, and a large cross-sectional dimension, N. In particular, the literature has focused on two GMM estimation techniques, namely, the first-difference GMM (proposed by Arellano and Bond, 1991 [37]) and the system GMM (see Blundell and Bond, 1998 [38]). For the instrumental variable for the continuous outcome variables (rates) we estimated the following form:

$$y_{it} = \beta_0 + \beta_1 y_{i,t-s} + \beta_2 m_{it} + \beta_3 m_{i,t-s} + \beta_4 x_{it} + \beta_5 T_t + \alpha_i + \varepsilon_{it} \ (4)$$

where β_0 is a constant; $y_{i,t-s}$ are the lags of the dependent variables, $m_{i,t}$ is the main explanatory variable, X_{it} includes local authority level covariates; α_i are the fixed effects[21],and ε_{it} is the idiosyncratic disturbance term.

In our analysis, this model has been estimated using the system GMM method because it leads to the result with the lowest bias. Blundell and Bond (1998) [38] stated that first difference GMM often reports large finite sample bias[22] and poor precision in simulation estimation. If we choose a weak instrument, there is a high risk of finite sample bias, even with large samples, as the findings can be distorted (or biased) [39]. The system GMM method considers a system of equations one in first-difference and one in level, where the instruments of the equation in levels are suitable lags of their own first differences, such as $\Delta y_{i,t-s}$. This approach has to satisfy the condition of absence of correlation between the instruments (first difference lags) that are also uncorrelated with the regression residuals. The Hansen J test, which is reported in this paper, is the test of over identifying restrictions and it is used to verify this condition. The null hypothesis is the absence of a correlation between the instruments and the regression residuals. Furthermore, in this kind of model the risk of

[21] Given the presence of fixed effects, these models do not include the deprivation index and the percentage of black and minority.

[22] A good estimator should satisfy three properties: unbiasedness, efficiency and consistency. An estimator is unbiased when its expected value is equal to the true value of the parameter estimated.

over-instrumenting the equation is quite high, i.e. using the lags in levels and in first-difference could generate a large number of instruments leading to biased results. The Hansen J test reports the results for all the instruments together, but also for the different set of instruments concerning the equation in levels and that one in first-difference and can therefore help inform the selection of instruments for the models. Moreover, the validity of the internal instruments lagged for two or more periods requires the absence of autocorrelation in the disturbance term v_{it}. This autocorrelation in the error term is tested through the Arellano-Bond autocorrelation test, which verifies the presence of autocorrelation for all the available lags.

Sensitivity analysis

We tested the robustness of our findings when controlling for the Better Care Fund (BCF). The BCF gave LAs additional funds for social care but was operational only in the final two years of our study (2015/16 and 2016/17).

Results

Full results of the models are available on request from the authors.

Descriptive analysis

Table 2 reports the descriptive statistics of all the variables used in our analysis. Data covered different financial years. Missing values most often occurred for the Isles of Scilly and City of London, whereas in the variables measuring the staff per head, the Isles of Scilly is included with Cornwall and City of London is included with Hackney.

Outcomes (healthcare utilisation)

In a typical LA during the study period, around 370 people over 65 were admitted to hospital annually with a fractured neck of femur (FNF) and around 460 people with dementia were admitted following a fall (Table 2). The rate of FNF per 100,000 population reduced over the study period due to rises in the population of older people rather than because of a decline in the number of cases (Figure 3). Nonetheless, the overall decline in the rates of both falls and FNF are unexpected and the reasons are unclear: whereas changes in coding practice might explain changes in the rate for falls, this is unlikely to be the case for changes in the rate of FNF.

Of hospital admissions for people with dementia, 39% lasted 7 days or longer on average and 15% lasted at least 21 days. In both outcome measures, the rates rose over time (Figure 3).

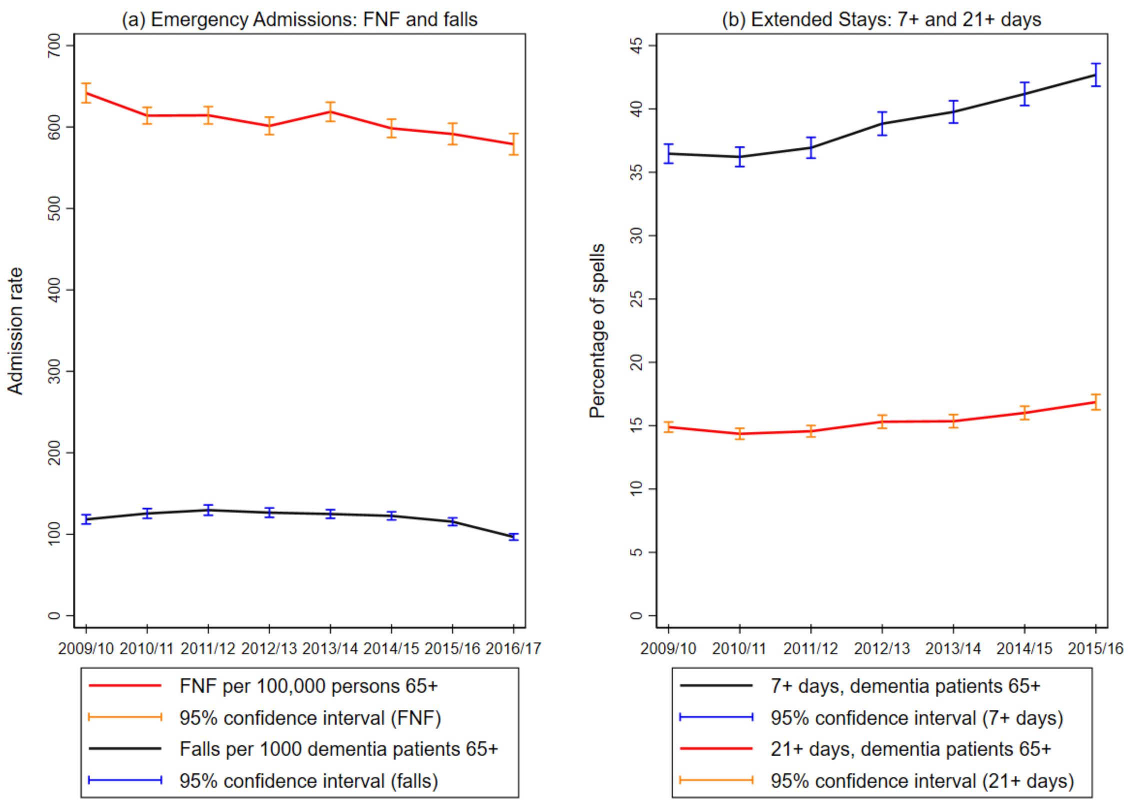

Figure 3: Outcomes: trends in emergency admissions for fall / FNF, and in extended stays

Notes: EA: Emergency admissions; FNF: fractured neck of femur; LoS: length of stay

The rate of those eligible for NHS Continuing Healthcare (NHS CHC) averaged 67 persons per 50,000 adults, but there was substantial variation across LAs (the rate ranged from 12 to 236). Figure 4 shows geographical variation in the rate in 2016/17. The rate was reasonably stable over the 4 years for which data were available (2013/14 to 2016/17).

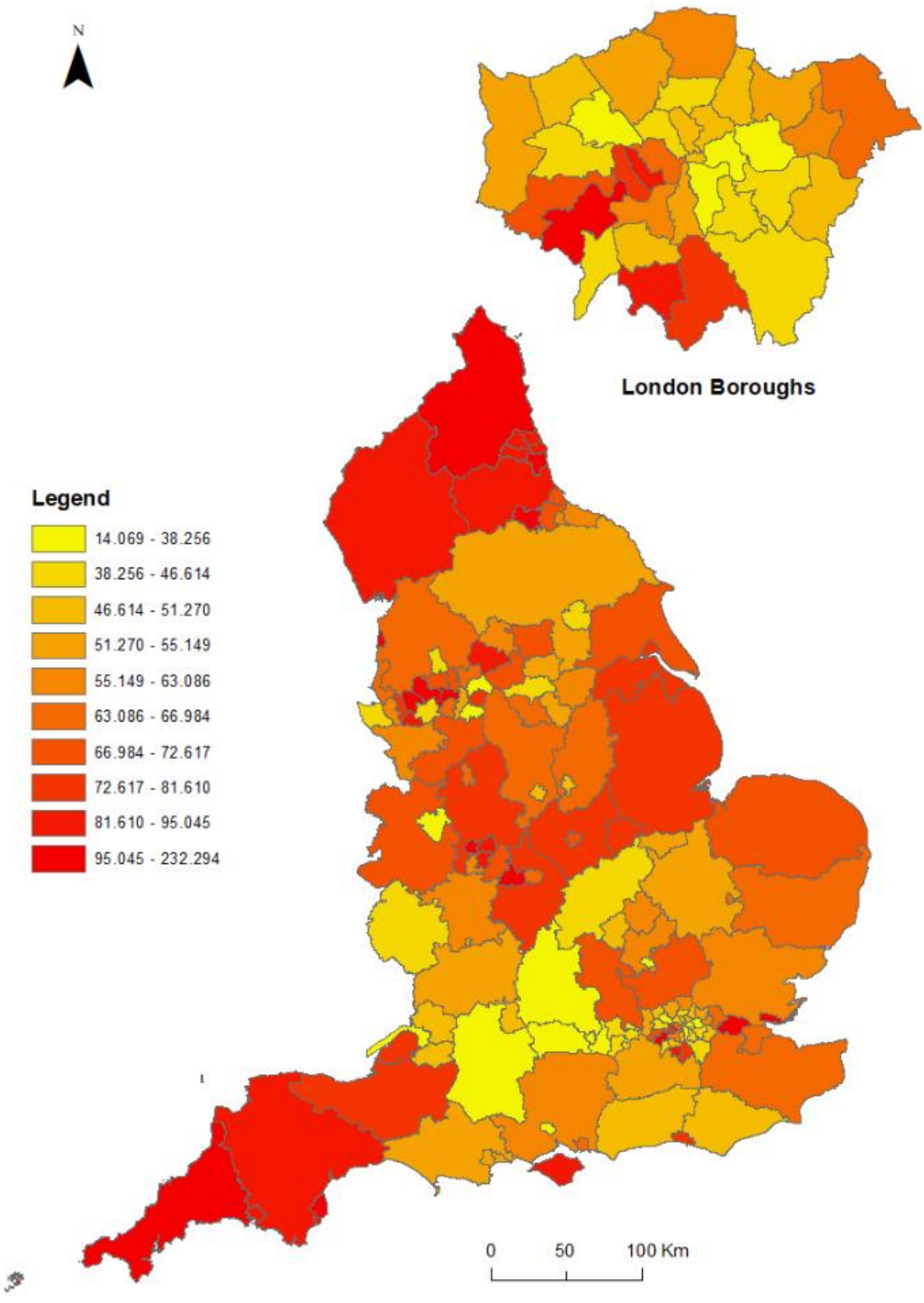

Figure 4: Geographical variation in NHC CHC – 2016/17

Social care measures
Over the period 2009/10 to 2016/17, the adjusted gross current spend on social care per person aged 65+ averaged around £950. Spend per head fluctuated over the study period, falling from £1,253 in 2009/10 to £825 in 2016/17, a reduction of 34% over seven years.

The level of social care staff providing care averaged 1.65 per 1000 adults for LAs; the corresponding figure for independent sector staff was much higher at 14.91. For LA staff, the rate fell over time whereas the rate of independent sector staff increased.

Details of the control variables are in Table 2, and Figure 5 illustrates trends in the social care supply measures.

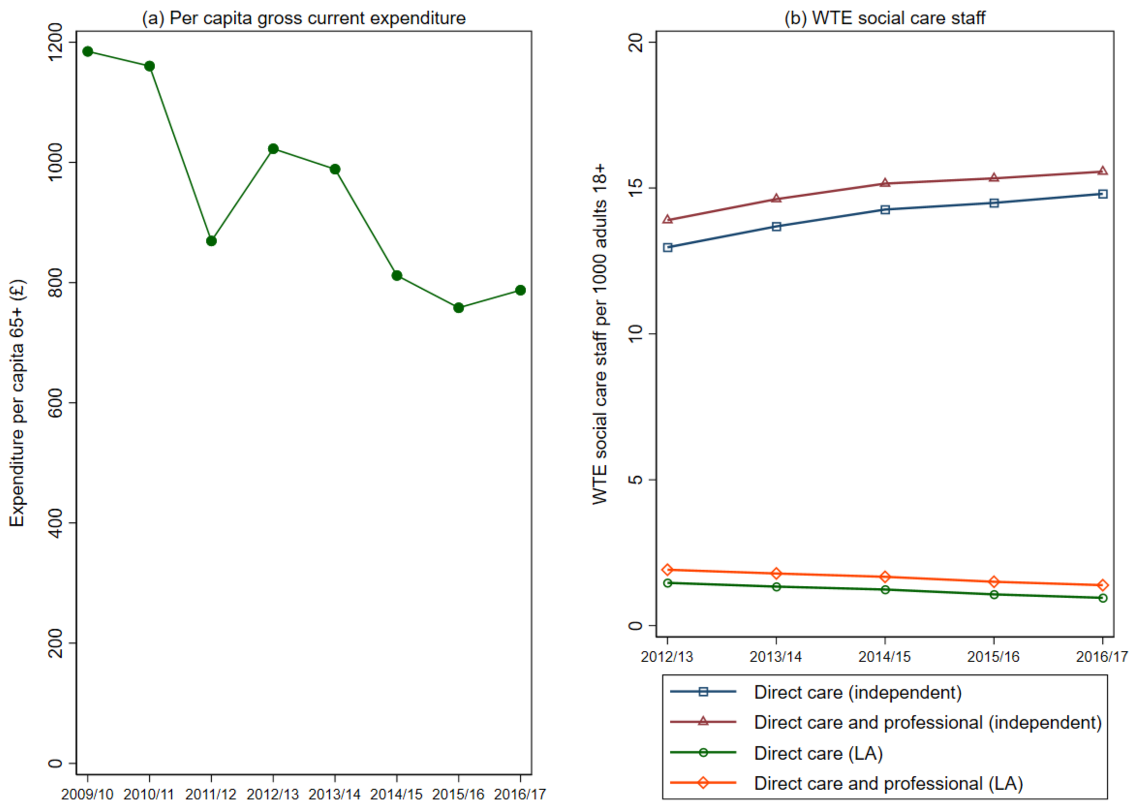

Figure 5: Key explanatory variables: (a) Mean per capita gross current expenditure adjusted by area cost for people aged 65+ and (b) Mean whole time equivalent (WTE) front-line social care staff at LA and independent sectors per 1000 persons aged 18+

Regression results

Table 4 provides a simple overview of findings. None of the measures of social care supply (expenditure or staffing) was significant in explaining emergency hospital admissions for fractured neck of femur (FNF) or falls. Results for the other measures of utilisation were inconsistent.

Table 4: Overview of regression results

	Outcomes				
Measure of Social care supply	**FNF**	**FALLS**	**7+**	**21+**	**NHS CHC**
Gross expenditure pp, adjusted (age 65+)	ns	ns	+	ns	ns
Gross expenditure pp, adjusted (3 age groups)	ns	ns	+	ns	ns
Gross expenditure pp, adjusted; Better care fund spend pp	ns	ns	ns	ns	ns
Staff (LA): direct care excl. professionals, medium	ns	ns	ns	ns	ns
Staff (LA): direct care excl. professionals, high	ns	ns	ns	ns	+
Staff (LA): direct care incl. professionals, medium	ns	ns	ns	ns	+
Staff (LA): direct care incl. professionals, high	ns	ns	ns	ns	+
Staff (indep): direct care excl. professionals, medium	ns	ns	-	ns	ns
Staff (indep): direct care excl. professionals, high	ns	ns	-	-	ns
Staff (indep): direct care incl. professionals, medium	ns	ns	ns	ns	ns
Staff (indep): direct care incl. professionals, high	ns	ns	-	-	ns
IV (area cost adjustment - ACA)	ns	ns	ns	ns	-
IV (dynamic panel)	ns	+	ns	ns	ns

Notes: Staff measured in terciles per capita aged 18+ (low / medium / high).
Age measured with 3 age groups (65-74; 75-84; 85+) unless otherwise stated.
ACA: area cost adjustment; FNF fractured neck of femur; 7+ [21+]: extended stay 7 [21] days or longer; NHS CHC: NHS continuing healthcare; pp: per person. + : sig. positive relationship; - : sig. negative relationship; ns: not statistically significant.

Table 5 to Table 8 summarise results for our key explanatory variables.

Expenditure, measured using gross current spend per head (adjusted by the ACA), was positively associated with extended stays of 7 days or more, but not associated with stays in excess of 3 weeks (Table 5). The effect of staffing on extended stays by people with dementia was mixed (Table 6). Our four staffing models (panels A to D) tested different combinations of measures of LA and independent sector frontline and professional social care staff. LA staffing levels were not associated with extended stays, but LAs with high levels of independent sector staff were associated with lower rates of extended stays.

LAs with higher levels of staff providing direct care (i.e. front-line staff), and/or higher levels of professional staff, were associated with higher rates of NHS CHC (Table 6).

We used the area cost adjustment (ACA) as an instrumental variable for gross current expenditure, which can be considered to be a strong instrument as the F statistic value is about 10 or higher in the first-stage estimation [32]. Expenditure was negatively related to rates of NHS CHC, but was unrelated to the other outcomes (Table 7).

Results from the dynamic panel model (Table 8) showed a positive association with the admission rate for falls and found no effect on other outcomes. The dynamic panel model is based on the idea of instrumenting the endogenous variable using their own lags (see section Dynamic panel model above). Roodman (2009) suggested as a rule of thumb that the Hansen J test's P-value should lie in the interval 0.1-0.25 [40]. The number of instruments must be less than the number of observations and there must be no autocorrelation in the error term. In Table 8, the Hansen J test is always within the interval, except in the models on the extended days.[23] The AR test for autocorrelation in the error terms, reported in Table 8, is a useful test to choose the number of lags that are better

[23] However, in these two models it was the best combination of instruments for the two equations. Basically, we instrumented the first difference equation with y_{it-2} and y_{it-3} and the equation in level with all the available first differences for the dependent variable and the main endogenous variable (expenditure).

instruments. This test is applied to the residual in differences, because $\Delta\nu_{it}$ is mathematically related to $\Delta\nu_{it-1}$ via the shared ν_{it-1} term, negative first-order serial correlation is expected in differences and evidence of it is uninformative. In other words, the AR (1) test is always expected to be significant, and the AR (2) test can be checked to see whether the first order lags can be used as instruments. Looking at the results reported in Table 8, none of the models reports serial correlation between the errors higher than the expected first-order serial correlation. All the models passed the AR(2) tests as indicated by the insignificant P-values, which shows that the serial correlation in the error terms is not second order. This indicates that all the lags are good instruments for the system of equations.

The relationship between unpaid care and outcomes (utilisation) is shown in Table 5, Table 7 and Table 8. Councils with higher rates of unpaid care had higher admissions rates for fractured neck of femur (FNF) but lower admission rates for falls and a lower proportion of hospitalised patients with extended stays of 21 days or more (Table 5, Panels A and B).

Table 5: Regression results: effects of social care expenditure

	(1)	(2)	(3)	(4)	(5)
	FNF	**Falls**	**7 +**	**21 +**	**NHS CHC**
Panel A: Gross expenditure pp (adjusted), age 65+					
Expenditure pp	1.000	1.000	1.000***	1.000	1.000
	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]
Unpaid care	1.003	0.988***	1.001	0.990**	0.992
	[1.000,1.006]	[0.982,0.994]	[0.997,1.005]	[0.984,0.996]	[0.981,1.004]
Obs	1203	1214	1063	1063	606
Panel B: Gross expenditure pp (adjusted), age 65-74; 75-84; 85+					
Expenditure pp	1.000	1.000	1.000***	1.000	1.000
	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]
Unpaid care	1.005***	0.987***	1.000	0.988***	0.993
	[1.002,1.008]	[0.981,0.994]	[0.997,1.004]	[0.982,0.995]	[0.981,1.006]
Obs	1203	1214	1063	1063	606
Panel C: Gross expenditure pp (adjusted), Better care fund spend pp, age 65-74; 75-84; 85+					
Expenditure pp	1.000	1.000	1.000	1.000	1.000
	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]	[1.000,1.000]
Unpaid care	1.006*	0.996	1.003	0.994	0.993
	[1.001,1.011]	[0.985,1.006]	[0.995,1.010]	[0.981,1.007]	[0.976,1.010]
Obs	299	300	150	150	300

Exponentiated coefficients; 95% confidence intervals in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: FNF fractured neck of femur; 7+ [21+]: extended stay of 7 [21] days or longer; NHS CHC: NHS continuing healthcare; pp: per person.

Table 6: Regression results: effects of the social care staffing levels

	(1)	(2)	(3)	(4)	(5)
	FNF	Falls	7 +	21 +	NHS CHC
Panel A: Direct care staff (LA), age 65-74; 75-84; 85+					
medium	0.996	0.988	0.994	1.004	1.030
	[0.980,1.012]	[0.961,1.015]	[0.979,1.009]	[0.979,1.029]	[0.979,1.085]
high	0.986	0.999	0.996	1.021	1.078*
	[0.966,1.006]	[0.964,1.036]	[0.976,1.016]	[0.987,1.056]	[1.013,1.147]
Obs	751	755	604	604	604
Panel B: Sum of direct care staff and professionals (LA), age 65-74; 75-84; 85+					
medium	0.995	0.986	0.996	1.002	1.060*
	[0.979,1.010]	[0.961,1.012]	[0.981,1.010]	[0.978,1.027]	[1.008,1.114]
high	0.992	0.999	0.988	1.016	1.092**
	[0.972,1.012]	[0.965,1.035]	[0.969,1.008]	[0.982,1.050]	[1.026,1.161]
Obs	751	755	604	604	604
Panel C: Direct care staff (LA and independent), age 65-74; 75-84; 85+					
medium (LA)	0.997	0.989	0.992	0.999	1.033
	[0.981,1.013]	[0.963,1.017]	[0.977,1.007]	[0.975,1.024]	[0.981,1.088]
high (LA)	0.986	1.001	0.993	1.017	1.081*
	[0.966,1.007]	[0.966,1.038]	[0.973,1.013]	[0.983,1.052]	[1.015,1.151]
medium (independent)	0.996	1.008	0.981*	0.985	1.027
	[0.977,1.015]	[0.975,1.041]	[0.963,0.999]	[0.956,1.015]	[0.970,1.087]
high (independent)	1.006	1.021	0.967**	0.939**	1.052
	[0.982,1.030]	[0.979,1.066]	[0.944,0.990]	[0.903,0.976]	[0.977,1.131]
Obs	751	755	604	604	604
Panel D: Sum of direct care staff and professionals (LA and independent), age 65-74; 75-84; 85+					
medium (LA)	0.996	0.987	0.994	0.999	1.063*
	[0.980,1.012]	[0.962,1.013]	[0.980,1.008]	[0.975,1.023]	[1.011,1.118]
high (LA)	0.992	1.000	0.987	1.013	1.097**
	[0.972,1.013]	[0.965,1.035]	[0.967,1.006]	[0.980,1.047]	[1.031,1.167]
medium (independent)	0.993	0.998	0.986	0.979	1.029
	[0.974,1.012]	[0.966,1.032]	[0.968,1.003]	[0.951,1.008]	[0.970,1.090]
high (independent)	1.013	1.028	0.973*	0.935***	1.016
	[0.990,1.038]	[0.986,1.073]	[0.950,0.995]	[0.900,0.971]	[0.944,1.093]
Obs	751	755	604	604	604

Exponentiated coefficients; 95% confidence intervals in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Regression results- IV method

	(1)	(2)	(3)	(4)	(5)
	FNF	**Falls**	**7 +**	**21 +**	**NHS CHC**
Expenditure pp	-0.035	0.019	0.000	0.001	-0.073**
	[-0.130,0.061]	[-0.018,0.055]	[-0.009,0.008]	[-0.002,0.005]	[-0.126,-0.019]
Unpaid care	1.841	-1.133*	-0.060	-0.127	-0.860
	[-1.319,5.002]	[-2.226,-0.041]	[-0.309,0.190]	[-0.290,0.036]	[-2.403,0.683]
Obs	1,203	1,214	1,063	1,063	606

95% confidence intervals in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Regression results - dynamic model

	(1)	(2)	(3)	(4)	(5)
	FNF	**Falls**	**7 +**	**21 +**	**NHS CHC**
Expenditure pp	0.144	0.042**	0.000	-0.001	-0.004
	[-0.070,0.358]	[0.014,0.070]	[-0.005,0.004]	[-0.004,0.001]	[-0.022,0.015]
L.FNF	0.133*				
	[0.013,0.253]				
L.Falls		0.922***			
		[0.718,1.126]			
L.7 Days+			0.794***		
			[0.511,1.077]		
L.21 Days +				0.757***	
				[0.422,1.092]	
L.NHS CHC					0.645***
					[0.345,0.946]
Unpaid care	1.843	-0.604***	-0.018	-0.032	0.478*
	[-1.018,4.704]	[-0.908,-0.300]	[-0.093,0.056]	[-0.105,0.041]	[0.012,0.944]
Hansen J test	4.844	6.329	3.656	4.138	4.162
Hansen J test: P value	0.184	0.176	0.454	0.388	0.245
AR (1) test	-7.23	-4.59	-3.08	-3.74	-1.70
AR (1) test: P value	0.000	0.000	0.002	0.000	0.089
AR (2) test	-0.47	1.31	0.23	-0.63	-
AR (2) test: P value	0.641	0.190	0.815	0.528	-
Obs	1050	1062	911	911	454
N. instruments	19	20	19	19	15

95% confidence intervals in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: L.var indicates a 1 year lag of the variable. Hansen test – see text for interpretation.

Sensitivity analysis

Adjusting for the impact of the Better Care Fund had no effect on these results, except that the positive association between spend and extended stays (7+) was no longer statistically significant. This apparent discrepancy may be due to the smaller number of observations available for analysis as only two years of BCF data were available.

Discussion

Overview of findings

The level of social care expenditure on older people was not significantly related to emergency admission rates for falls or fractured neck of femur. Extended stays of 7 days or longer were significantly and positively related to the level of social care spend, but this association was no longer significant when additional spend from the Better Care Fund was taken into account. There was no significant relationship between the level of social care spend and hospital stays of 21 days or longer or between spend and uptake of NHS CHC.

As an alternative to social care spend, we used social care workforce measures to capture changes in social care supply. LAs employing higher levels of front-line social care staff (especially professional staff) had significantly higher levels of NHS CHC, but there was no relationship between LA staffing levels and the remaining four outcomes. One possible reason why staffing is positively associated with CHC is that LAs have greater capacity to complete the assessments, which are complex and time-consuming. Alternatively, the provision of CHC by the NHS may enable LAs to employ more front-line staff. The mechanism behind this relationship is therefore unclear. LAs with higher levels of independent social care staffing had significantly lower rates of extended stays, but there was no effect on emergency admissions or on NHS CHC. The effect of 'full time' unpaid care on outcomes was mixed, with tentative evidence of a protective effect on admissions for falls, and on extended stays of 21 days or longer.

The use of instrumental variables did not support these findings. When the Area Cost Adjustment was used as an instrument in place of expenditure, results were inconsistent with the main analysis: there were negative effects on admissions for fractured neck of femur and on NHS CHC but no effect on any other outcome. The dynamic panel models found a positive relationship between spend and emergency admissions for falls, with the remaining relationships statistically insignificant.
There was therefore no conclusive evidence that LAs with higher rates of spend or that employed higher rates of social care staff had lower admission rates or shorter hospital stays. There was tentative evidence that higher rates of social care staffing by LAs was associated with higher rates of NHS CHC, and that LAs with higher rates of independent social care staffing had lower rates of extended stays. However, published activity data were insufficient to explore these nuanced issues in a reliable way.

What this study adds

This exploratory study linked multiple national datasets to analyse the effects of changes in social care provision – both expenditure and staffing – on a range of NHS outcomes. Previous studies have also focused on older people, but findings are mixed. Forder's 2009 analysis, based on electoral wards, identified cost substitution effects between residential long-term care and hospitals and vice versa. Seamer et al (2019) analysed a 10-year panel of data covering 132 LAs. They found no relationship between social care spend and two broad 'front-door' measures of hospital utilisation, emergency admissions for any reason and for ambulatory care sensitive conditions. Their findings were robust to different model specifications [41]. Crawford and colleagues (2018) used a six year panel of data from 143 LAs to test for an impact on Accident and Emergency (A&E) utilisation. Lower social care spend - which they instrumented using a Bartik approach – was associated with significantly higher A&E utilisation, particularly in people aged 85 and over [42].

Our study offers several methodological advances. First, with support from our advisory group, we selected utilisation measures that could plausibly be influenced by the supply of social care. We also tested a wider range of measures than previous studies, including both 'front-door' hospital measures (admissions for falls and for fractured neck of femur) and 'back door' measures (extended length of stay). To the best of our knowledge, we are the first to examine the association between social care expenditure and staffing and the uptake of NHS CHC which is a vital component in determining the care experience of older people, as well as the impact on resource use. We also explored the feasibility of analysing impacts on deprivation of liberty safeguards (DoLS) and mental health delayed transfers (DToCs) but were unable to proceed due to data inadequacies. However these are important outcomes and by highlighting the gaps in the data we hope to stimulate improvement in data sources which would allow further research to be undertaken.

Second, unlike previous studies that have focused on changes in social care expenditure [41, 42], we used two approaches to measuring social care supply – gross current expenditure on older adults, <u>and</u> workforce measures for both LA employees and the independent sector. We used gross (rather than net) current expenditure, because this takes account of local capacity to raise funds from clients, which allow LAs to cross-subsidise care for the most vulnerable clients. We adjusted spend to reflect variations in local purchasing power, to make the interpretation of our results more comparable. Further, we conducted sensitivity analysis to test the added impact of the Better Care Fund, money that is not captured by the annual financial returns, which we modelled separately from gross current expenditure to disentangle its effects.

As labour is the main factor of production in social care, we would expect the impacts of social care expenditure to mirror the impacts of staff supply. However, our analyses showed that the effects of the two types of social care supply can, and do, differ (Table 4). Higher levels of LA staffing were linked to higher rates of NHS CHC, and higher levels of independent sector staffing were associated with lower rates of extended stay, but the outcomes were not linked to social care expenditure. As there are no published data on the proportion of WTE staff working with older client groups, staffing rates were based on adult populations (18+).

Third, we used instrumental variables (IV) to tackle the potential problem of endogeneity ('reverse causality') – this may arise if local decisions on social care spending are informed by the supply and quality of local NHS services. We tested two IV approaches. We used the labour element of the Area Cost Adjustment as an instrument, which performed well. We also used a dynamic panel model, which incorporates lags of outcome measures as well as lags of the explanatory variable of interest. Crawford and colleagues compared standard regression (OLS), a fixed effects (FE) model, and instrumental variables (a Bartik approach) [42]. Like us, they found results were sensitive to choice of model, with results from the OLS and FE inconsistent with those from the IV model.

Lastly, the analyses controlled for the provision of informal care, which is an important confounding factor when attempting to isolate the effect of formal social care on NHS use. Crawford and colleagues used the Carers Allowance data to generate a measure of informal care [42]. We improved on this measure, restricting it to working age adults rather than all adults – this is because many older full time carers do not apply for the benefit as their state pension makes them ineligible. To obtain a more complete picture of the prevalence of informal care, we combined data on the recipients with those who were eligible but did not receive the allowance. This provided a measure of 'intensive' carers that can be viewed as a 'tip of the iceberg' measure of informal care, capturing the proportion of <u>working-aged</u> individuals who provide care for at least 35 hours a week, i.e. the caring role is effectively full time.

Limitations

A key limitation of these analyses is that social care data were available only at the level of the local authority. As there is no routine collection of individual-level data on formal and informal social care it was not possible to test whether individuals who received social care were at lower risk of hospitalisation, extended stay, or access to NHS CHC. This is a problem known as an ecological fallacy, which arises when inferences about individuals are based on inferences about the group to which they belong. Therefore, our findings do not imply that changes in an individual's social care receipt have no impact on their healthcare utilisation or on their health or wellbeing.

Significant unexplained variability in hospital utilisation measures remained after adjusting for a range of confounding factors, probably reflecting differences in patient case mix that are not captured by area level measures. For example, we selected our 'target' group of people with dementia (the focus of three of our five outcome measures) as those likely to require both health and social care, but this group is also likely to have multimorbidity – this factor is a potential confounder in our analyses.

Our analyses were unable to identify how LAs spent their budgets, i.e. variations in the types and levels of service delivery. Two LAs with the same level of spend may provide very different services, and target different subgroups of clients and these differences are likely to influence healthcare utilisation.

Lastly, our study covered the period up to 2016/17 (due to data availability). It is possible that local authorities had sufficient reserves, or were able to make cuts elsewhere, to allow them to protect adult care social services for older people during this time. However, it is not clear whether they were able to continue to do so subsequently.

Future research / policy implications

Our findings suggest the workforce capacity of LA employed social care staff may be a factor in influencing geographical access to NHS CHC. This finding is somewhat counterintuitive: our a priori expectation was that access would be higher in areas with lower levels of front-line staff providing social care. It is possible that social care staff in LAs with higher staffing ratios have greater capacity to provide an 'advocacy' role in negotiating their clients' need for NHS CHC; if so, this may free up local social care budgets allowing LAs to provide more care to other residents. A simpler alternative explanation is that the provision of NHS CHC by the NHS enables LAs to employ more front-line staff. However, we cannot rule out the possibility that the quality of NHS CHC data is too poor to support robust analyses.

We found tentative evidence that higher levels of social care provision by the independent sector and by unpaid carers may have had a protective effect on older people in terms of reducing the rates of extended stays in hospital. If these other types of social care are substituting for cuts to formal sector social care provision, it begs the question of how sustainable these substitutes are.

Higher use of privately funded social care may not be affordable for individuals in the longer term once their savings have run out; and the effect of Brexit on the independent sector workforce remains unclear at the time of writing. The proportion of working aged people providing 'intensive' (35 hours a week or more) levels of unpaid care has grown in recent years (Figure 2), but whether and for how long this trend will continue remains to be seen. There may also be policy tensions between reliance on unpaid carers to 'plug the gap' in social care, and planned changes in State Pension age. It is therefore of value to revisit this research question in future years to test whether or not the independent and informal care sectors have had an important effect in averting adverse impacts on the NHS and, if so, how durable this protective effect has been.

Future research requires comprehensive and better quality data, ideally at the level of the individual. The priority is to establish a collection of routine data on individuals' use of health and social care – including use of informal care and private sector care. Not only would this support a robust analysis of the relationship between social care funds and healthcare utilisation, it could also help providers to deliver personalised, integrated care. Second, measuring impacts on health outcomes and wellbeing or quality of life would also require bespoke collections. The Patient Reported Outcome Measures (PROMs) data for elective surgery – e.g. hip and knee replacement – are a potential data source, but analyses would need to control carefully for healthcare quality in order to isolate the impact of social care. Without information on health outcomes and wellbeing, the benefits and harms of policies remain opaque. Third, improved coding of hospital sites within the Hospital Episode Statistics could shed light on whether intermediate care facilities are an efficient and effective means of reducing extended stays. Finally, adult safeguarding data could help explore additional unintended consequences associated with reductions in social care funding.

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